

Climate forecasting services: coming down from the ivory tower

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Francisco J. Doblas-Reyes^{1,2}, Louis-Philippe Caron¹, Nicola Cortesi¹, Albert Soret¹, Verónica Torralba¹, Isadora Christel¹, Marta Terrado¹, Nube González-Reviriego¹ and Marco Turco¹

¹Earth Sciences Department, Barcelona Supercomputing Center (BSC), Spain, ²Institució Catalana de Recerca i Estudis Avançats (ICREA), Spain

Introduction

Subseasonal-to-seasonal (S2S) climate forecasts are able to provide added value across a range of application areas (energy, water management, agriculture, health, insurance) through tailored climate services. This contribution highlights the value of services through several examples of their application in the **energy**, **(re-)insurance** and **agriculture** sectors.

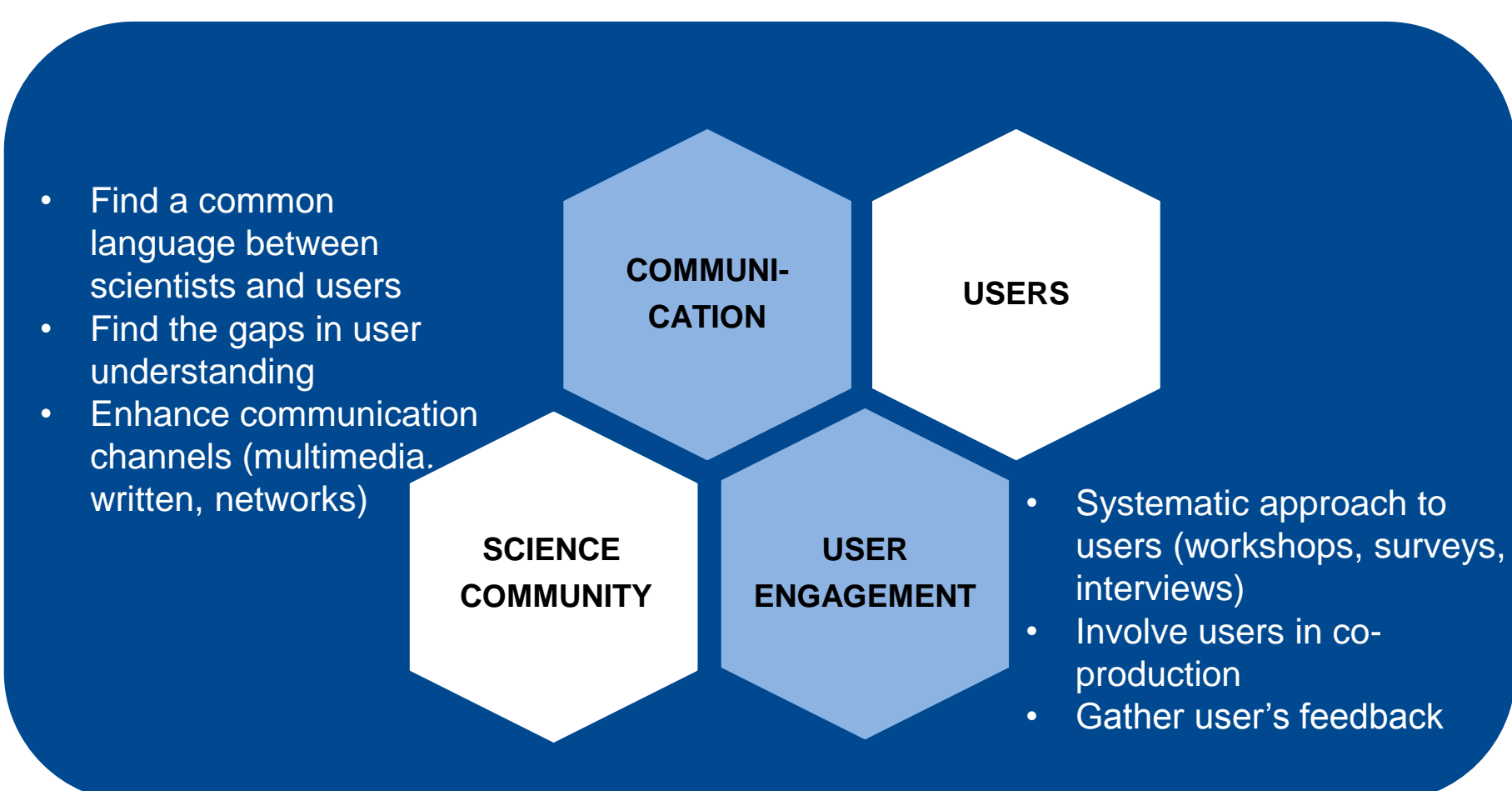
From climate data to climate information:

Applied research in climate services makes use of **observational datasets** to provide the assessment of uncertainty through innovative methods (e.g. [1]) that provide novel ways to use gridded observations (e.g. [2]) or state-of-the-art reanalyses (e.g. [3]). There is also a large number of operational dynamical **S2S forecast** systems developed in the framework of EUROSIP [4], SPECS project, the North American Multi-Model Ensemble (NMME [5]) or experimental forecast systems developed at the Barcelona Supercomputing Center (BSC; e.g. [6]).

Climate services should make climate information available but also easier to use by providing **software tools**, such as open-source R packages for statistical analysis and data mining in climatology. For instance, s2dverification is a tool developed and maintained by the BSC that facilitates seasonal to decadal data verification.

Most of this is possible thanks to high-performance computing (HPC) systems. BSC hosts a range of HPC systems including **MareNostrum III**, one of the most powerful supercomputers in Europe with 48,128 cores and 1.1 Pflops capacity.

From climate information to climate knowledge:



Climate services aim to make climate information **action oriented**. To reach a real co-design and co-production of users, climate services require a **multidisciplinary approach** that includes communication and user engagement to transform climate information into climate knowledge.

Seasonal prediction of extremes

The forecast quality of **extremes** is generally similar to or slightly lower than that of monthly or seasonal averages of the underlying variable (see e.g. Figures 1 and 2), but such forecast offers information more relevant **to specific user needs**.

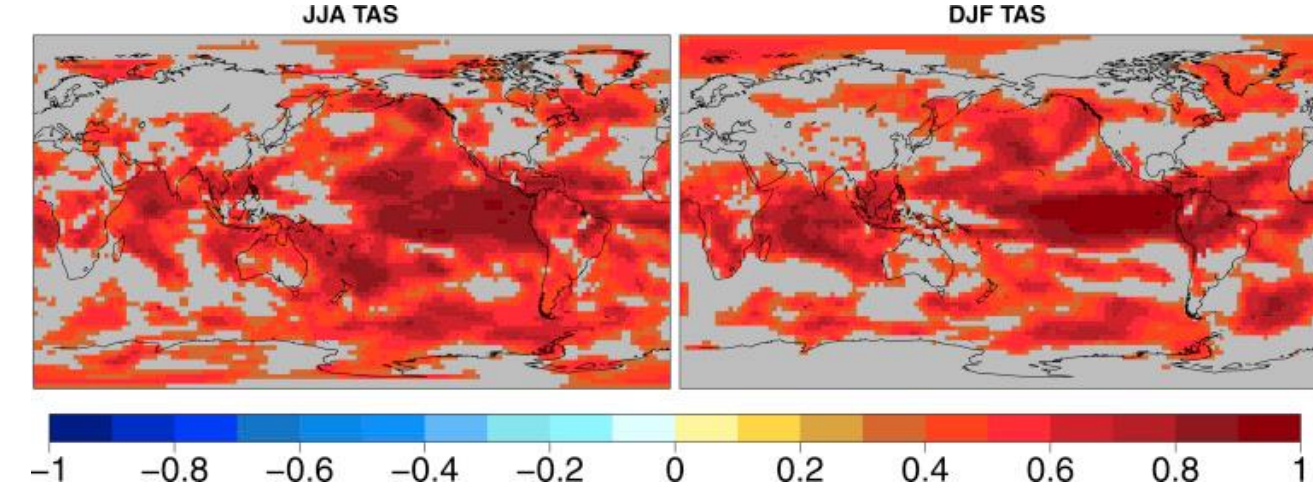


Fig 1: Anomaly correlations between the ENSEMBLES multi-model forecast of the ensemble mean temperature and ERA-Interim reanalysis for JJA (left) and DJF (right), 1979-2005. Correlations are only shown where they are significant at the $p=0.05$ level using a Fisher test that takes into account the effective number of independent data. Source: [7].

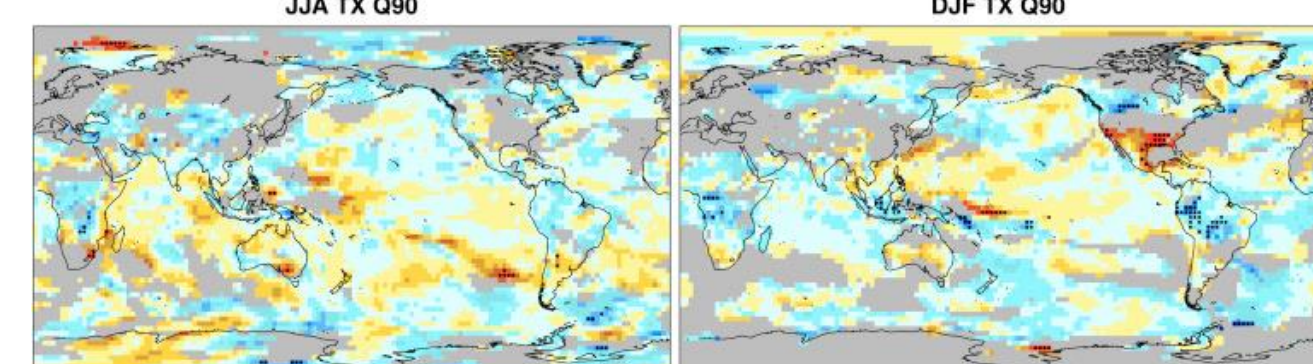


Fig 2: This figure shows the areas where the skill of forecasts of extreme temperature is higher or lower than forecasts of the seasonal average. Differences are only shown for regions where either the correlation for the seasonal mean temperature or the temperature extreme of interest are statistically significant, while black dots indicate areas where the difference between correlations is statistically significant. Correlations are calculated over the period 1979-2005 for the JJA (left) and DJF (right). Source: [7].

Seasonal prediction for wind energy

The aim of climate services is to create **tailored climate information using a multidisciplinary approach**. For instance, **Project Ukko** (<http://project-ukko.net>) is an on-line tool (or User Interface Platform) that has been developed in close collaboration with data visualization specialists and designers to provide **seasonal wind speed predictions**. The map in Figure 3 is an example of the standard scientific way of providing seasonal predictions but, collaborating with other disciplines, it is also possible to find alternative and more intuitive ways of providing climate information. This tool has been created as part of the prototype developed within the **EUPORIAS** project but our services group is also developing visualization tools for the Copernicus project **Clim4Energy** or the H2020 project **PRIMAVERA**.

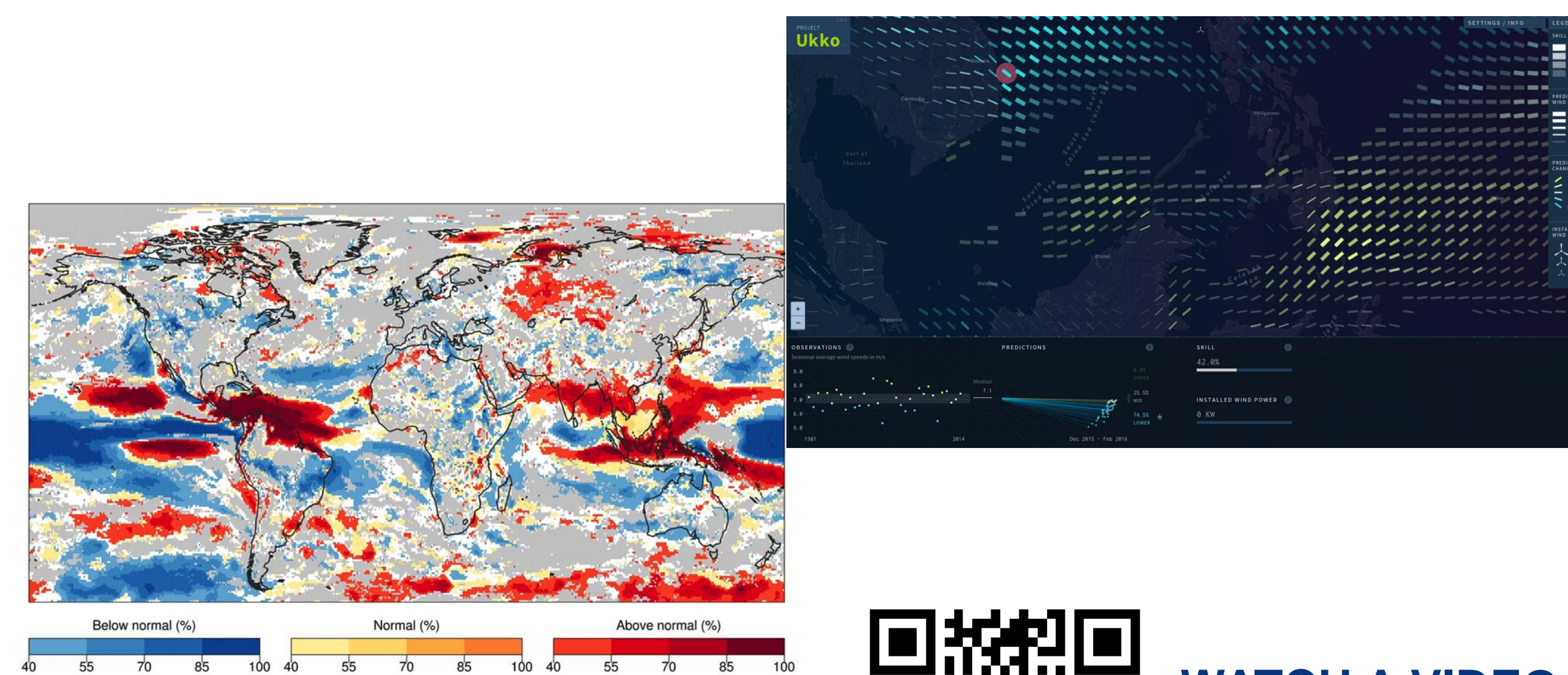


Fig 3: Wind speed seasonal prediction. Coloured areas show the most likely wind speed category (below normal, normal and above normal) and its percentage probability to occur. These categories show where the model improves upon the current approach using the climatology. White areas show where the probability is <40% and approximately equal for the three categories. Grey areas show where the model does not improve upon the current approach, which assumes that the future will be a repetition of the past. Source: Torralba et al. (under review)



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Using large-scale climate indices

The services group also performs research on industry-relevant topics, such as identifying the **climate drivers of seasonal variability**. This example (Figure 4) illustrates the areas where El Niño or the North Atlantic Oscillation (NAO) have a significant **impact on surface wind speed**.

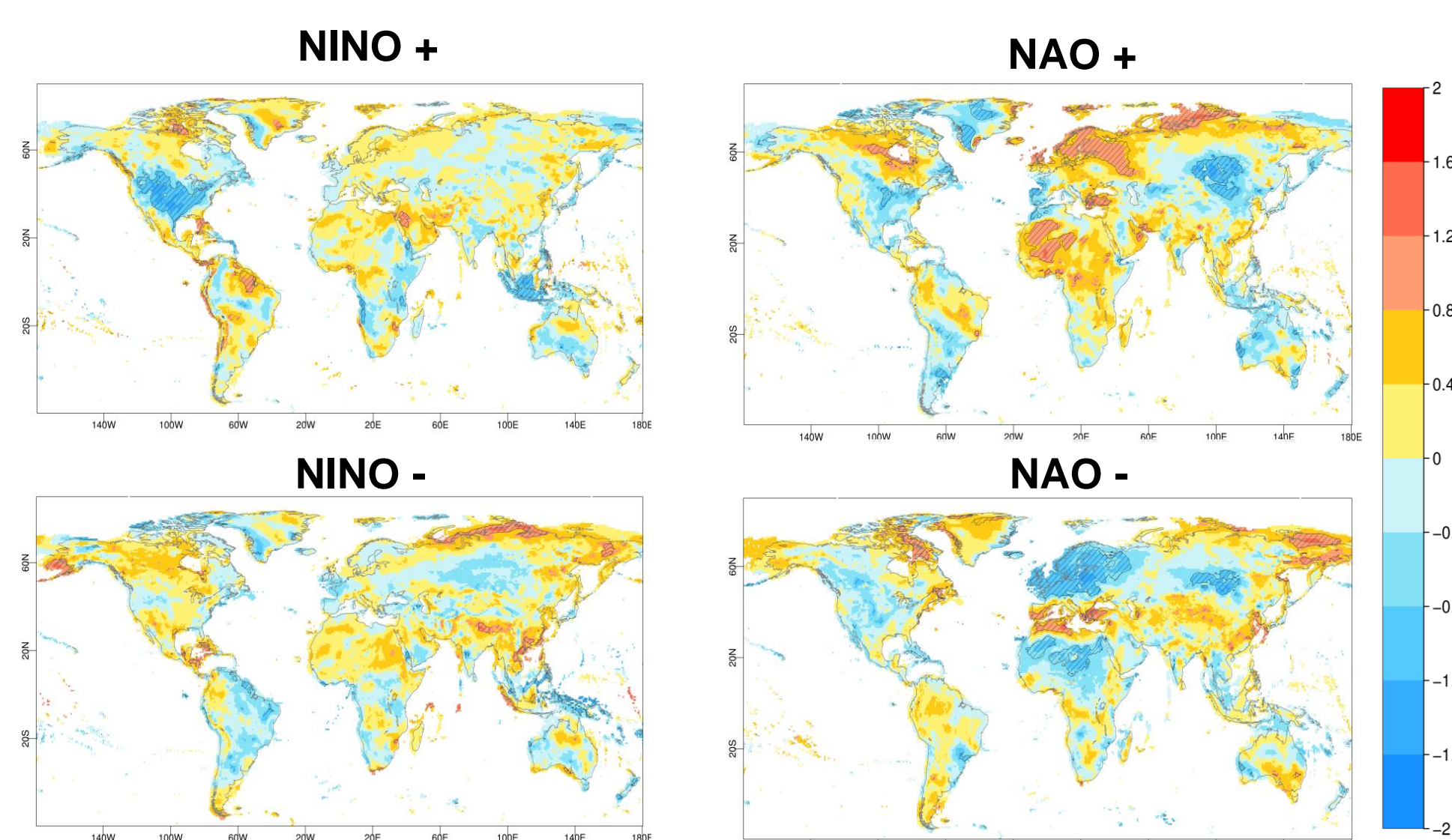


Fig 4: Impact maps of the NINO 3.4 index and NAO index (pc-based) on 10-m wind speed from the ERA-Interim reanalysis in DJF for the period 1981-2015. Red areas indicates an increase of wind speed and blue areas show a decrease. These indices help illustrating the relative merits of climate forecast information to users and are the cornerstone of climate stories that engage them in the co-production of climate information. Hatched areas show where the relationship is significant at a 95% confidence level.

Seasonal prediction for agriculture

Concurrent drought-heatwave events strongly impact ecosystems and human societies. The European summer of 2003 is a good example of this, with unusually intense heatwaves and concurrent drought conditions leading to **extensive agricultural losses**. Figure 5 shows that the regions where drought is predicted with high probability are consistent with the observed droughts.

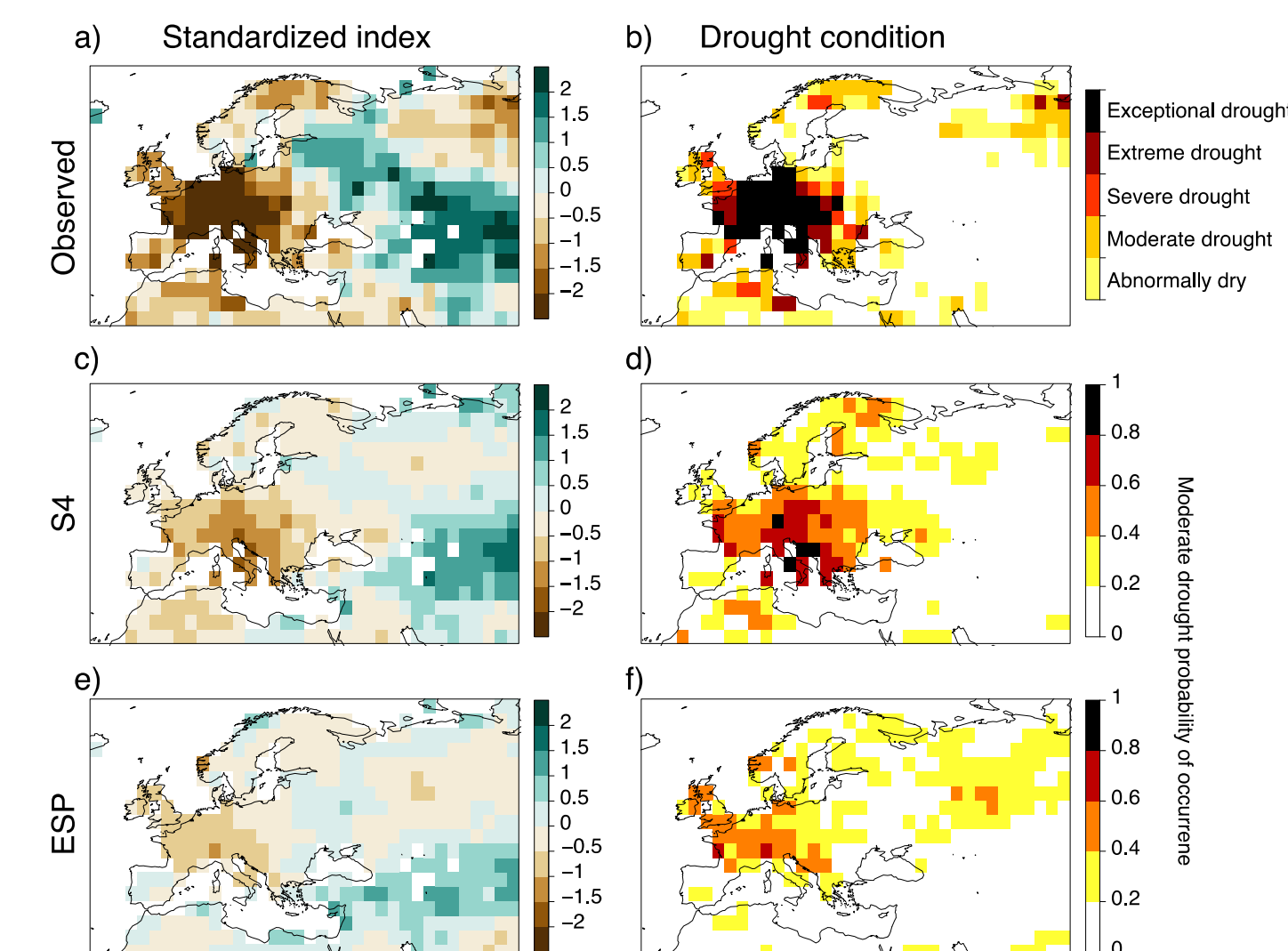
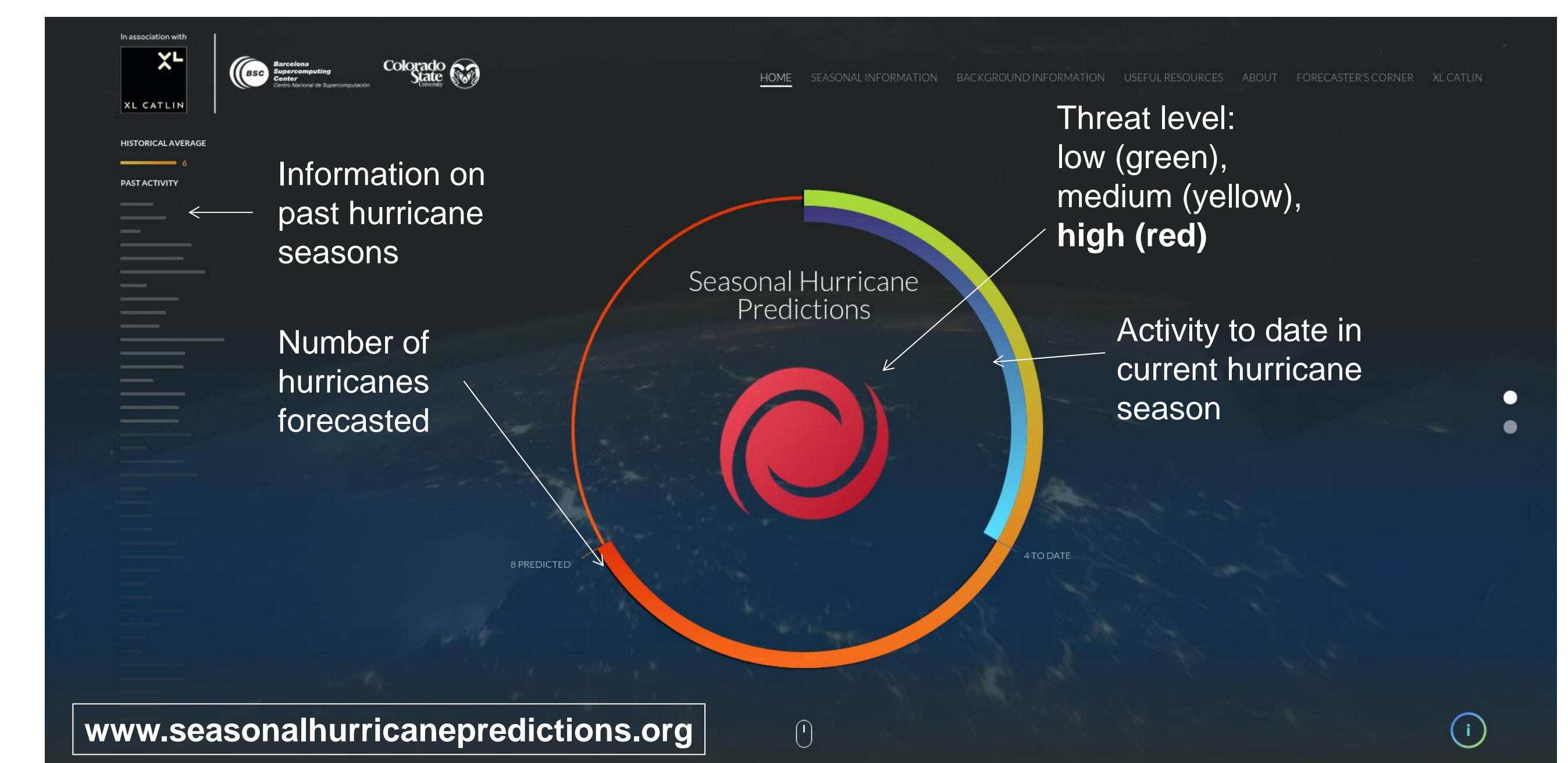


Fig 5: Observed 6-month SPEI for August 2003: a) SPEI6 values and b) observed drought conditions. Predicted SPEI6 for August 2003 with the start date of May: c) S4 ensemble mean; d) S4 probability for moderate drought occurrence (SPEI<0.8); e) ESP ensemble mean and f) ESP probability for moderate drought occurrence. SPEI: Standardized Precipitation Evapotranspiration Index, based on the simultaneous use of precipitation and temperature data (see <http://sac.csic.es/spei/> for more details). S4: ECMWF System 4; ESP: Ensemble Streamflow Prediction, a baseline empirical method that relies on resampled historical data to generate an ensemble of possible future climate outlooks. Both methods merge observation of precipitation and temperature with the seasonal forecasts of those variables to predict drought indicator. Source: Turco et al. (in preparation)

Seasonal prediction for the (re-)insurance sector

Tropical cyclones rate as the primary meteorological phenomena in the context of causing destruction and economic losses. As such, forecasting the upcoming level of hurricane activity is a prime concern for the (re-)insurance sector. The BSC has partnered with the Colorado State University and XL Catlin to offer a platform offering the most up-to-date view of upcoming Atlantic hurricane activity. The site also offers in-depth analyses of these forecasts.



References

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